Separation of Heart Sounds & Lung Sounds using Independent Component Analysis

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Abstract: **Auscultation is the most common way of physical examination of a patient by a physician. Recently, in order to develop automated home care system and to assist physician getting better auscultation results; electronic stethoscope and computer analysis have become an inevitable trend. On this account a fuzzy expert system based body sounds analysis kit designed by HemaKumar [1]. In this existing kit, the interface part design is the most important aspect. The problem with the existing design is that it needs separate channels for heart and lung sounds to be analyzed by the fuzzy model. Such separation of heart and lung sounds becomes very much important for an acute care physician in an ICCU (Intensive Coronary Care Unit).**

In this study, to separate the two signals, a novel Heart sound (HS) separation method based on Independent Component Analysis (ICA) is developed. This method applies an ICA algorithm to the spectrograms of two simultaneous lung sound recordings obtained at two different locations on the chest and yields the independent spectrograms of the separated signals. Then, by implementing the Inverse Short Time Fourier Transform, the separated signals are reconstructed in the time domain. The method was applied to data of 25 healthy subjects. Analysis of the results indicates the efficiency of the proposed method in terms of HS separation from lung sounds.

Keywords: Human heart and lung sounds, Electronic stethoscope, Fuzzy expert system, Independent Component Analysis.

1. Introduction

Acoustical analysis of lung sounds provides important and helpful information in the diagnosis and monitoring of lung diseases.

Clinical interpretation of lung sounds however is obscured at frequencies below 150 Hz due to the intrusive quasi-periodic interference of heart sounds (HS) [2]. For respiratory sounds, HS is considered as noise and there have been many studies to reduce or remove HS from lung sounds recordings. On the other hand, for the cardiologists the main signal of interest is HS and lung sounds are considered as noise. Therefore, a method that can separate the two signals would be of great interest for both groups of researchers.

Lung sound and HS signals are considered as independent source signals. However, due to the delays and reflections of the lung tissues, the mixed signals recorded on the skin are correlated and are not of instantaneous mixture nature but are convolutive mixtures. One solution to separate this type of mixed signals is to apply Independent Component Analysis (ICA) on the spectrograms of the recorded signals. Hence, the objective of this study is to investigate the application and feasibility of ICA on HS separation from lung sounds.

II. Methodology

Lung sound and HS signals can be considered as unknown independent source signals, but their resultant measured signal on the skin is a response of convoluted signals applied on the transmission media. Thus HS separation from lung sounds can be considered as a multichannel blind deconvolution problem [3].

Assuming n sources produce respiratory sounds and HS, a sound record over the chest can be denoted as a source matrix $S(t)$ consisting of n source signals as:

$$S(t) = [s_1(t), \ldots, s_n(t)]^T \tag{1}$$

Where $s_j(t)$, $j = 1, \ldots, n$ are assumed to be independent of each other. Without loss of generality, it is assumed that $S(t)$ is zero mean. The n source signals are assumed to be delayed, filtered and mixed while they are transmitted through the medium (i.e., skin, lung and heart tissues) before being picked up by an array of n sensors on the skin. These simultaneously recorded signals can be represented by a matrix called the observation matrix:

$$X(t) = [x_1(t), \ldots, x_n(t)]^T \tag{2}$$

Where $x_i(t)$, is the recorded signal at sensor i, which can be expressed as:

$$x_i(t) = \sum_{j=1}^{n}\left(\sum_{\tau} a_{ij}(\tau) s_j(t-\tau)\right) = \sum_{j=1}^{n} a_{ij}(t) * s_j(t), \quad (3)$$

Where * denotes convolution and a_{ij} represents the transfer function of the transmission path from the source j to the sensor i. The equation (3) can be represented in generalized matrix format as:

$$X(t) = A(t) \otimes S(t) \quad (4)$$

$A(t)$ can be considered as a filter matrix and $\otimes$ is a symbol which indicates a_{ij} is convolved and not multiplied with $s_j(t)$.

The relationship between the observations and the source matrices can be presented in the Time-Frequency (TF) domain by employing the Short Time Fourier Transform (STFT) [4]

$$\hat{X}(\omega, t_s) = \hat{A}(\omega)\hat{S}(\omega, t_s), \quad t_s = 0, \Delta T, 2\Delta T, \ldots \quad (5)$$

Where $\hat{A}(\omega)$ is the Fourier transform of $A(t)$, $\hat{S}(\omega, t_s)$ is the STFT or commonly called the spectrogram of the source matrix $S(t)$ and ΔT specifies the shifting time.

Joint Approximate Diagonalization of Eigen-matrices (JADE) algorithm was selected for solving these non-convolutive mixture subproblems. JADE is one of the ICA algorithms on complex valued data and is an appropriate candidate for our case since the spectrogram of a breath sound is complex. Since the recorded signals are generally distributed over a non-orthogonal direction in the coordinates, before applying the JADE algorithm, prewhitening should be implemented, to rearrange these directions such that the recorded signals become orthogonal to each other in a new coordinate system [5].

Implementing the JADE algorithm at each frequency will then yield the independent components at that frequency. This can be represented in a matrix format as:

$$\hat{U}(\omega, t_s) = \hat{B}(\omega)\hat{X}(\omega, t_s), \quad (6)$$

Where $\hat{B}(\omega)$ is the Fourier transform of a demixing filter $B(t)$ and $\hat{U}(\omega, t_s)$ is the STFT of the estimated source signals. If $B(t)$ is a perfect inverse filter of $A(t)$, then $U(t)=S(t)$. However, due to the lack of information about the amplitude and the order of source signals, there will be ambiguities about scaling factors and permutation

The optimum $\hat{B}(\omega)$ satisfies the following relationship:

$$\hat{U}(\omega, t_s) = \hat{B}(\omega)\left(\hat{A}(\omega)\hat{S}(\omega, t_s)\right) = PDS(\omega, t_s), \quad (7)$$

Where D is a diagonal matrix representing scaling factors and P is a permutation matrix. In the permutation matrix at frequency ω, all the elements of each row are equal to zero except for one element with value 1, where the column number corresponds to the source order number. In order to avoid the scaling indefiniteness, instead of estimating the source signal, the problem can be moderated to find decomposition as:

$$\hat{X}(\omega, t_s) = \hat{V}_1(\omega, t_s) + \hat{V}_2(\omega, t_s) + \ldots + \hat{V}_n(\omega, t_s), \quad (8)$$

Such that each $\hat{V}_i(\omega, t_s)$ is the STFT of the signal $V_i(t)$,originated from the i^{th} independent source and $V_I(t)$ are mutually independent. Using the filter $\hat{B}(\omega)$ and its inverse at frequency ω, the desired decomposition $\hat{V}_i(\omega, t_s)$ can be defined as:

$$\hat{V}_i(\omega, t_s) = \hat{B}(\omega)^{-1} E_i \hat{B}(\omega)\hat{X}(\omega, t_s) \quad (9)$$

Where E_I is a diagonal matrix with = 1 E_{ii} and zero for all the other elements [6]. Where i=1,…,n, should be equal to identity matrix I. For reconstructing the independent source signals in the time domain, proper independent components at each frequency should be chosen and combined with each other, i.e. the permutation problem should be solved before reconstructing the independent source signals [6]. Finding such an appropriate combination is only possible for nonstationary signals, which is the case in this study. This is due to the correlation that exists between the components of a non-stationary signal at different frequencies. In fact, the non stationarity of the signal causes its amplitude at each frequency ω to change in time corresponding to the envelope of the signal at that frequency. Since at frequency ω, the i^{th} and j^{th} source signals are uncorrelated, and different frequency components of different source signals are also uncorrelated, calculating the correlation coefficient of different source signal envelopes at different frequencies, will resolve the permutation problem.

By combining the proper independent components from each frequency, the spectrograms of the separated signals are produced. Afterwards, by implementing Inverse Short Time

Fourier Transform (ISTFT) the separated signals are reconstructed in the time domain.

III. DATA ACQUISITION

Twenty five healthy volunteer subjects in two groups around the age group of 25 to 30 years participated in this study. Physiograph was used to record the lung sounds. The subjects were asked to maintain low flow rate, by monitoring their breathing on oscilloscope display. This was then repeated at a medium flow rate. The breath sound signals were amplified and band pass filtered from 50-2500 Hz and digitized at 10240 Hz using 16 bits per sample.

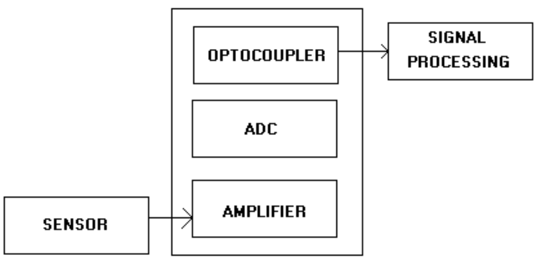


Figure 1 Signal acquisition & processing

IV. IMPLEMENTATION OF ICA-BASED METHOD

The spectrograms of the signals at each flow rate, $\hat{X}(\omega,t_s)$, was calculated by applying the discrete STFT to every 100 ms segment (1024 samples) of data using a Hanning window. Since a small overlap may lead to a wrong solution, the overlap between adjacent segments was chosen as 85% of the segment length. Considering the fact that the recording was on healthy subjects, without any adventitious sounds such as crackles and wheezes, the number of sources are assumed to be equal to two (n=2). Then ICA-based technique was applied to the spectrograms and the separated signals were obtained.

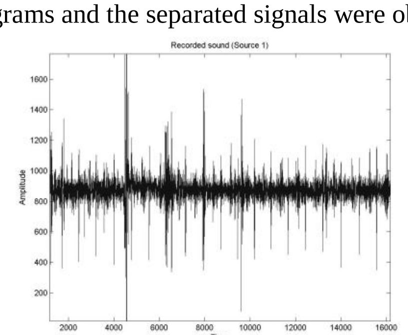


Figure 2 Recorded signal from L chest (Sen 1)

V. DISCUSSION & RESULTS

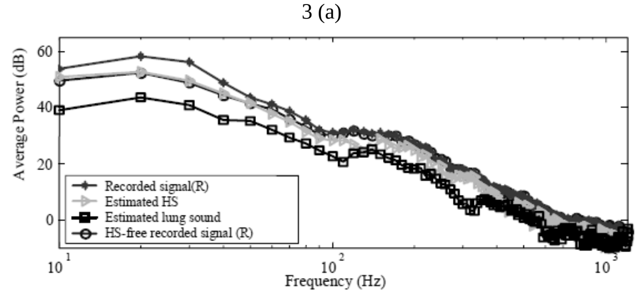
This proposed method is applied on two recorded signals. HS and LS are separately estimated. The quantitative analysis of the results is usually based on the standard approach of comparing the average Power Spectra Density (PSD) of segments of lung sound with and without HS with the average PSD of segments of estimated lung sound.

Based on this validation approach, it was found that the average PSD of the estimated lung sound signal falls between the average PSD of HS-free segments and the average PSD of the recorded signal including HS and it would be closer to the former than to the latter. However, for our study, one has to be careful when using this validation approach. This is because in our study the estimated source signals $S(t)$ may be different from the recorded signal $X(t)$, i.e., $X(t) \neq S(t)$ due to the convolution effect with the impulse response of the fat tissue and skin medium. However, if the impulse response of the medium is an ideal impulse function (or resembles that function), the average PSD of estimated source signals ideally would be equivalent to (or not significantly different) from those of HS-free signal.

Figure 3 shows the average PSD of the recorded signals, the two average PSD's of the estimated HS and of the lung sound signals (obtained using the proposed HS separation method) and the average PSD of the recorded signals free of HS. These four averages are obtained over the medium flow rate.

Since the HS is not a continuous signal, there are segments in the recorded signal that are free of HS. Therefore, the reference spectra of HS-free segments were selected manually by listening to the recorded signals and further confirmed by visually inspecting the spectrogram of the signals. The average PSD of the estimated lung sound signal was found to be lower than that of the HS-free recorded lung sounds. This confirms the success of proposed technique in terms of HS reduction from lung sound recording.

3 (a)



3 (b)

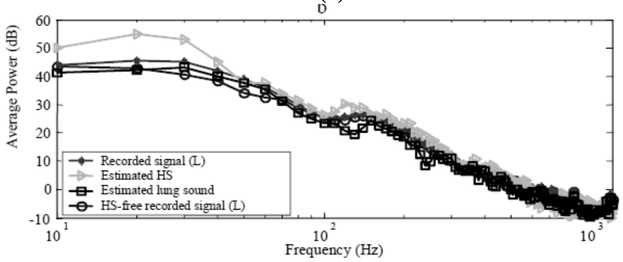


Figure 3 (a) & (b) Comparison between the average PSD of the estimated HS and lung sound signals using the proposed method and that of lung sound signal with and without HS, recorded at R (sensor1) & L (sensor2) locations of the chest.

Figure. 4 (a) & 4 (b) show the spectrograms of the lung sound signals recorded simultaneously from R (sensor 1) and L (sensor 2) locations on the chest at low flow rate and Fig. 4 (c) & 4 (d) illustrate the spectrograms of the estimated HS from sensors 1 and 2, respectively. Figure. 4 (e) & 4 (f) depict the spectrograms of the estimated lung sound from sensors 1 and 2, correspondingly. As can be observed from the spectrograms of the estimated lung sound, the average power of the segments corresponding to HS has been reduced over low frequencies, which convey the fact that the estimated lung sound is free of HS. Listening to the estimated lung sound signals confirmed that the HS were significantly reduced even though they were not completely cancelled. Also from listening to the result signals, it was observed that the estimated HS had less lung sounds (but still included weak lung sounds)

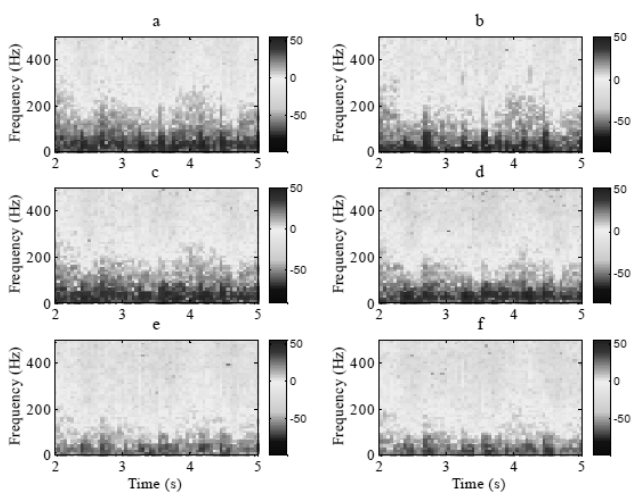


Figure 4 Spectrograms of the recorded signals at R and L locations (Fig. 4 (a) & 4(b)) and the estimated HS (Fig. 4 (c) & 4 (d)) and lung sound signals (Fig. 4 (e) & 4 (f))

Slight difference was found between the HS-free portions of recorded signals and the corresponded portion of estimated lung sound signal. This might be due to the separation of the third and forth HS from lung sound using this method. Since these sounds are not audible, the manually selected HS-free portions of recorded signals may contain them.

Two simultaneous recordings have been used for separating the lung sounds from HS without considering the noise at the sensors. Thus, the use of more simultaneous recordings may improve the results by separating the additive noises as well as HS from the lung sound recordings [6]. Although this may be considered as a drawback but in cases where multiple simultaneous recordings are required for diagnosis purposes, applying the suggested method for HS separation with more simultaneous recordings might be beneficial.

VI. CONCLUSION

In summary, the spectrogram ICA-based method could significantly reduce the HS but not completely cancel it from the estimated lung sound recordings. The estimated lung sounds also look slightly different from the HS-free observed ones. This is expected since the ICA technique estimates the recorded source signals; (i.e. in our case the lung sound before passing through the medium of fat tissues and skin) and these signals are slightly different from the recorded ones. The proposed method separates LS & HS efficiently better than existing methods. Thus ICA technique can be used in HILSA kit to separate HS and LS.

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